

A NEW MARKOVIAN PREDICTION SCHEME FOR RESOURCE RESERVATIONS IN WIRELESS NETWORKS WITH MOBILE HOSTS

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Abstract. Nowadays, mobile service requests in wireless networking are aimed to the benefit of a good level of satisfaction for the received Quality of Service (QoS) guarantees. In this paper, a new prediction algorithm is proposed, for the pre-reservation of passive bandwidth, when mobile users moves under radio coverage that can be considered as a cellular one (GSM, UMTS, WLAN clusters, etc.). The Hidden Markov Chains (HMC) theory is used to design the predictor, as the main component of the proposed idea, that does not depend on the considered transmission technology, mobility model or vehicular scenario. Mobile ReSerVation Protocol (MRSVP) has been used in order to realize the active/passive bandwidth reservation in the considered network topology. Different simulation campaigns have been carried out in order to appreciate the benefits of the proposed idea.

Keywords

Hidden Markov model, MIP, mobility, MRSVP, overview, pattern prediction, prediction.

1. Introduction

In this paper, we considered QoS issues of mobile communications in wireless networks. Mobility Independent Predictive users (MIP), [1], are considered and their service requests can be considered as non-tolerant: low call-dropping probability, service continuity and low delay-jitter must be guaranteed. At the best of our knowledge, a good way to avoid service degradations during hand-over events is represented by passive-reservations [1], [2], [11], that is to say, when a mobile user makes a service request on the current coverage cell, the admission control should ensure bandwidth availability on all the cells that the mobile hosts will probably visit during its session.

The MRSVP is able to guarantee the right

communication among the interested coverage cells, while the predictor is mandatory in order to know exactly which are the cells where the mobile host will hand-in. The mobility model has a heavy impact on the obtained results: in this paper we employed the Smooth Random Mobility Model (SRMM), [3], as well as the C4R mobility generator [4], in order to appreciate prediction performance when mobility traces are synthesized or extracted from real roadmaps and they can be unrealistic if the model is not appropriate. As earlier stated, the proposed technique is of general application and does not depend on the specific coverage technology: combining MRSVP and HMC as described in the following, a new prediction scheme is proposed and its performance are stated through a deep campaign of simulations.

The paper is organized as follows: section 2 gives a deep overview of the Mobile ReSerVation Protocol and the basics of Hidden Markov Chains theory, section 3 proposes the new prediction scheme, section 4 shows simulations results and section 5 concludes the paper.

2. Mobile RSVP and System Model

The RSVP is used on other network platforms in order to allow bandwidth reservation to system terminal. It has been extended several times in order to accommodate different needing: for example, the Aggregate-RSVP has been implemented, in order to manage reservations in hybrid platforms such as satellite/terrestrial operating with two different QoS architectures [13]. Again, in order to handle users mobility and to offer guaranteed services (independent from mobility) the ReSerVation Protocol has been extended with the MRSVP [1]; in this way, the hand-off events can be managed in an adequate manner and the mobile users can make reservation requests over more than one cell, by their proxy agents: there are local proxy agents (which handle the active reservations) and remote proxy agents (which deal with passive reservations).

An active reservation is made by a user only on the current access point, while passive reservations are

made only on the remote cells that the user will visit during its connection (users belonging to Mobility Independent Predictive, MIP, class requests passive reservations). A MRSVP connection starts with a proxy-discovery protocol phase, with which the user can know the addresses of its remote agents; then a resource request can be made, which will reach the net sender, in order to begin data packets transmission. After the proxy addresses are discovered, users send active_RESV messages to their local access points and passive_RESV messages to their remote access points, so the system must effect an admission control, in order to accept or refuse users' requests. When a user moves from a coverage area to another one, the hand-off event is managed by a reservation switch: the reserved resources in the old access point are released and the passive resources can be assigned by switching to an active reservation. For more details about MRSVP see [1].

Figure 1 describes the MIP active and passive reservations (on the current cell and on the passive ones) in a simplified 1D scenario, hypothesizing that the user knows the cells that he will visit during its active connection; this information is carried out by the MRSVP through the exchange of the MSPEC message [1], but the use of a prediction algorithm is necessary, when users move among a two-dimensional (2D) set of cells. Dotted lines in Fig. 1 represent passive reservation requests.

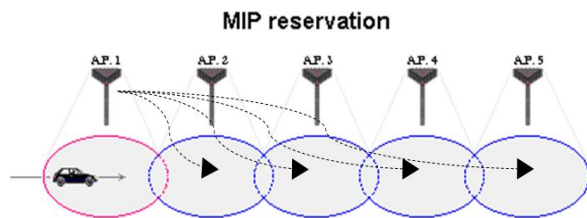


Fig. 1: An example of passive reservation.

As earlier described, in this work the MRSVP has been integrated with the HMC, because the passive_RESV messages have to be sent only to the remote cells that a mobile host will probably visit: each intermediate coverage cell has to know which is the neighboring cell where the mobile host will hand-in. The HMC is a statistical model used for modeling generative sequences that can be characterized by an underlying process generating an observable sequence. Formally, a HMC can be described by a triplet λ as follows:

$$\lambda = (A, B, \pi). \quad (1)$$

Defining S as the set of possible states $S = \{s_1, s_2, \dots, s_N\}$, with $\|S\| = N$ and V as the observations set $V = \{v_1, v_2, \dots, v_M\}$ with $\|V\| = M$, then a finite state sequence $Q = q_1, q_2, \dots, q_T$ and a corresponding observation sequence $O = o_1, o_2, \dots, o_T$ can be defined, with $\|Q\| = \|O\| = T$. The first term in Eq. 1 is a transition array, which stores the probability of state j following state i , independent from time:

$$A = [a_{ij}], a_{ij} = P(q_t = sj / q_{t-1} = s_i). \quad (2)$$

The second term is the observation array, storing the probability of observation k being produced from the state j , independent of t :

$$B = [b_i(k)], b_i(k) = P(x_t = v_k / q_t = s_i), \quad (3)$$

and π is the initial probability array:

$$\pi = [\pi_i], \pi_i = P(q_1 = s_i). \quad (4)$$

In addition to the Markov chain dependence property, for the HMC there is another assumption for the model, for which the output observation at time t is dependent only on the current state and it is independent of previous observations and states:

$$P\left(\frac{O_t}{O_{t-1}^{t-1}}, q_t^t\right) = P\left(\frac{o_t}{q_t}\right). \quad (5)$$

In this paper, a HMC is used by each coverage cell to forward passive_RESV messages to the predicted neighboring cell. Details about learning, evaluation and decoding can be found in [5], [6]. Now, a brief description of the considered system is given, then the application of a particular HMM to the cellular network is introduced.

3. HMC Integration and Proposed Algorithm

Let C be the set of coverage cells of the considered wireless network, $C = \{c_1, c_2, \dots, c_c\}$ with $\|C\| = c$, then for each cell $c_i \in C$, with a coverage radius cr_i , a set of neighbouring cells $Adj(c_i)$ can be defined, on the basis of network topology and cell adjacencies. A generic coverage cell, generally with a circular shape, can be approximated with a n -edge regular polygon as depicted in Fig. 2 (n can be considered as an input control parameter).

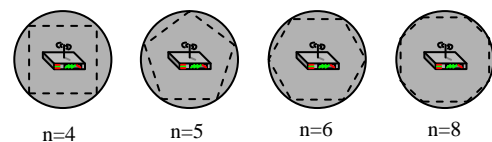


Fig. 2: Possible area approximation with regular polygons.

A set S_{ho} of n possible movement directions can be then obtained: let us indicate them with $d_1 \dots d_n$, where $d_j = \theta(2j-1)/2$ rad, $\theta = 2\pi/n$ rad and $j = 1 \dots n$, so $S_{ho} = \{d_1, \dots, d_n\}$ and $\|S_{ho}\| = n$. In the classical approaches on cellular networks [7], n is set to 6, so in this work $\|Adj(c_i)\| = \|S_{ho}\| = 6, \forall c_i \in C$. Let us suppose that each cell $c_i \in C$ has the availability of L bandwidth channels and each user occupies one channel in the current c_i ; that is to say that the maximum number of active users in a

cell is L . Our attention is not focused neither on the Call Admission Control (CAC) nor on the Bandwidth Reallocation Scheme (BRS) of the system, but only on the prediction of next neighbouring cells, through a HMC. So, we considered the simplest implementations, which provides that each mobile user will receive the same bandwidth level, related to the assigned channel on the cell, for the entire flow duration and a cell can accommodate a bandwidth request only if $l_{ci} < L$, where l_{ci} is the number of currently occupied bandwidth channels on cell c_i . In addition, the number of predicted hand-over events n_{ho} can be evaluated and users mobility has been considered through [4].

In fact, in [2], after many stochastic analyses, we demonstrated that the time spent by a mobile host in a cell (Cell Stay Time; CST) can be approximated by a Gaussian distribution. So the general expression of the CST p.d.f. is:

$$f_{X_{CST}}(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \quad (6)$$

where $\mu = \mu_{CST}(\nu, R)$ and $\sigma = \sigma_{CST}(\nu, R)$ are respectively the average and standard deviation of the Gaussian distribution, R represents the coverage radius and ν the average host speed; thus it is possible to evaluate the error of considered C.S.T. and to make a cell stay time prediction based on confidence intervals and confidence levels, considering the worst case Cell Outage Probability (COP). It is possible to select a cell stay time T_{CST} for a mobile host so that $Prob(X < T_{CST}) < 1-COP$, where X is normally distributed. T_{CST} is called a $(1-COP) \cdot 100\%$ upper confidence bound for X . If the average Call Holding Time (CHT) T_{CHT} is known, it is possible to consider the term N_{PC} (Number of Predicted Cells) as follows:

$$N_{PC} = \frac{T_{CHT}}{T_{CST}}. \quad (7)$$

So it is possible to use the N_{PC} value to make the pre-reservation of MIP flows, for $n_{ho} = N_{PC} - 1$ times, in order to leave more bandwidth availability in the not visited cells for new MIP flows. At this point, in the PASSIVE_RESV message an additional field “ res_{ho} ”, indicating the number of residual predicted hand-over events, can be added and the active cell (where the call has originated), can evaluate NPC as in eq. 7. Then, if $n_{ho} \geq 2$ (at least 1 hand-over events have been predicted), the active cell prepares a PASSIVE_RESV packet to be forwarded to the predicted neighbour by setting $res_{ho} = n_{ho} - 1$. Figure 3 illustrates the behaviour of c_i when a service request is received.

As defined in [1], when a cell receives a resource request, it has to perform the CAC: in the considered case it only verifies if $l_{ci} < L$. If there are no available channels ($l_{ci} = L$), then the request cannot be accepted and a RESV_NACK message is sent toward mobile host. If a channel can be assigned and c_i is the last predicted cell

($res_{ho} = 0$), it only has to send a positive RESV_CONF message toward mobile host. On the other hand, if more hand-over events have been predicted ($res_{ho} \neq 0$) for the considered mobile host, the cell uses a HMC predictor to know which is the neighbouring cell to forward a passive_RESV message to, after the res_{ho} value has been decreased by 1; at the same time, the cell sends a RESV_CONF toward the mobile host. At this point, the active cell knows the bandwidth availability on the predicted path for the mobile host, if no RESV_NACK messages have been received.

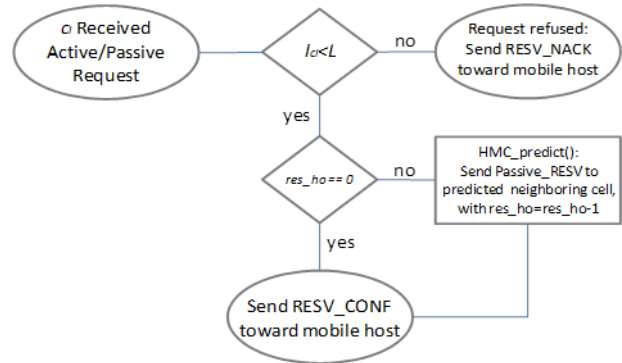


Fig. 3: Cell behaviour after the receipt of a reservation request.

Now the HMC system modeling is described. Hidden Markov Model is used in many fields of research [6], like automatic control, artificial intelligence, finance and biology. We hypothesize that, in the considered wireless cellular system, mobility management is performed by coverage cells. So what mobility prediction concerns is just user's path from entering the covering area of a cell to leaving. In this work two modeling schemes are considered.

3.1. Centralized HMC Model (CHMC)

In this case, a single HMC is considered for the whole system. A graph $G = \langle V, E \rangle$ is associated to the cellular network, where V is the set of vertices and E is the set of edges. Each vertex $v_i \in V$ represents a coverage cell $c_i \in C$, then $\|V\| = \|C\| = c$. The set E contains the edges that can be considered as the neighboring relationships of cells:

$$E = \{(v_i, v_j) / v_j \in Adj(v_i), \forall v_i \in V\},$$

$$\|E\| = \sum_{v_i \in V} \|Adj(v_i)\|. \quad (8)$$

At this point we considered the obtained graph as the state transition map of the HMC.

Figure 4 illustrates an example of mapping between a cellular system with $c = 24$ and its related graph G . As it can be seen, we considered a HMC with states s_i associated to vertices v_i , so $\|S\| = \|V\| = \|C\| = N = c$. In the centralized model, the entire path followed by a mobile node is considered as a sequence of cells and the issue of mobility prediction can be considered as a problem related to stochastic

processes. For example, if a mobile host hands-over from cell c_1 to cell c_5 , then a state transition from s_1 to s_5 has occurred.

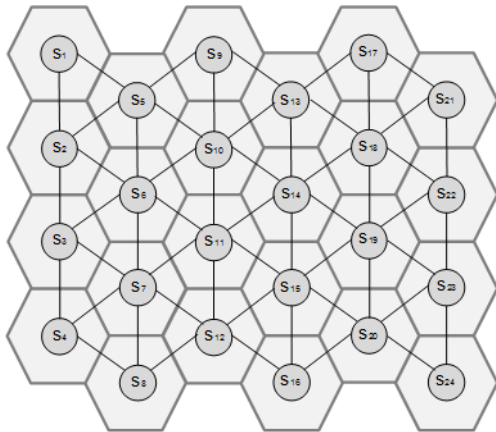


Fig. 4: System modeling for the centralized case with $c = 24$.

3.2. Distributed HMC Model (DHMC)

In the second case, each cell does not have knowledge of the whole system. A dedicated HMC, as illustrated in Fig. 5, is associated to each cell. In this case, the HMC for a generic cell $c_i \in C$ has a number of states equal to $n = ||S_{ho}||$, that is to say each state is associated to a possible hand-off direction. In this case, for example, a state transition from s_1 to s_5 occurs if a mobile host enters the cell from d_1 and hands-out to d_5 .

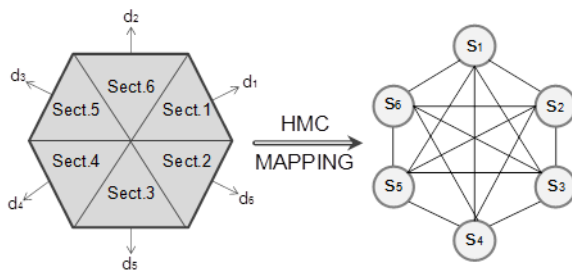


Fig. 5: HMC structure for the distributed case with $N = n = 6$.

3.3. HMC Learning, Prediction and Utilization

Based on classic theory on HMC and Baum-Welch algorithm [8], λ has to be determined, because it represents the triplet that defines the model for both schemes (CHMC and DHMC). Because observations of mobile hosts movements are possible (in our case by a system simulator, as explained in the next section), supervised training can be approached, because HMC inputs and desired outputs are known. Training observations consist in a set of the mobile host paths and hand-over direction sequences for CHMC and DHMC respectively. Having a high number of training observations of mobile hosts paths and directions, the Maximum Likelihood Estimates (MLE) can be used for the evaluation of A , B and π as follows:

$$a_{ij} = P(s_j | s_i) = \frac{TR(s_i | s_j)}{TR(s_i)}, \quad (9)$$

$$b_i(k) = P(v_k | s_i) = \frac{OCC(v_k, s_i)}{TR(s_i)}, \quad (10)$$

$$\pi_i = P(q_1 = s_i) = \frac{OCC(q_1 = s_i)}{N(q_1)}, \quad (11)$$

where $TR(s_i, s_j)$ is the number of observed transitions from state i to state j and $N(s_i)$ is the number of transitions from state s_i to any other state. For the CHMC, a transition from s_i to s_j occurs when, in the training data, a mobile host hands-over from cell c_i to cell c_j , while for the DHMC it occurs when a mobile host hands-in a cell from direction d_i and hands-out to direction d_j . The term $OCC(v_k, s_i)$ in Eq. 10 represents the number of occurrences of state s_i in the observations v_k . For the CHMC, state s_i occurs in the observation v_k if cell c_i is contained in the k -th path of the training data, while for the DHMC it occurs if the direction d_i is contained in the k -th hand-over sequence of the training data. The term in eq. 11 represents the probability that state s_i (coverage cell c_i or hand-over direction d_i) is the first observed state (q_1) in the training observations and it is evaluated as the ratio between the number of occurrences of s_i being the first observed state $OCC(q_1 = s_i)$ and the number of total observations of first states $N(q_1)$. So, λ can be evaluated through a supervised training.

At this point, given the HMC model expressed through the triplet λ , we need to evaluate $P(O|\lambda)$, that is to say the probability of the observation sequence O given the model λ . The probability of O for a specific state sequence Q can be expressed as:

$$P(O | Q, \lambda) = \prod_{t=1}^T P(o_t | q_t, \lambda) = b_{q_1}(o_1) \cdot b_{q_2}(o_2) \cdot \dots \cdot b_{q_T}(o_T), \quad (12)$$

and the probability of the state sequence is:

$$P(O | Q, \lambda) = \pi_{q_1} a_{q_1 q_2} a_{q_2 q_3} \dots a_{q_{T-1} q_T}, \quad (13)$$

so:

$$P(O | \lambda) = \sum_Q P(O | Q, \lambda) \cdot P(Q | \lambda) = \sum_{q_1 \dots q_T} \pi_{q_1} b_{q_1}(o_1) \cdot a_{q_1 q_2} b_{q_2}(o_2) \cdot \dots \cdot a_{q_{T-1} q_T} b_{q_T}(o_T). \quad (14)$$

If the forward-backward algorithm is introduced to evaluate the expression of eq. 14, the complexity is reduced from $2TN^T$ to N^2T [5], [8].

In the centralized case, the state associated to the cell where the mobile host has made its service request becomes the current state of the CHMC, so the current state is known. When the mobile user sends the ACTIVE_RESV, the current cell consults the centralized and shared CHMC model, starting the prediction of states

(cells) sequence through the evaluation of $P(O/\lambda)$ by eq. 14. In the distributed case the current state is represented by the hand-in direction d_i , and the DHMC is consulted by its own coverage cell in order to know the predicted hand-out direction (in this case, for the first prediction the hand-in direction is substituted by the mobile host born sector, where the call originated; sectors subdivision is illustrated in Fig. 5).

4. HMC Integration and Proposed Algorithm

Many simulations have been carried out in order to evaluate the performances of the proposed idea in terms of average prediction error, channel assignments, call dropping probability and call blocking probability. The considered scenario consists of a set of cell clusters, for a total of $c = 35$ coverage cells, depicted in Fig. 6 where, for example, real paths of Calabria's east-coast (south Italy) have been considered through the C4R mobility simulator [4] with a $900 \times 900 \text{ m}^2$ map. All the cells have the same coverage radius $cr_i = r$, $\forall i \in C$ and an exponentially distributed CHT with mean $\lambda = 180 \text{ s}$ has been considered. In the simulation scenario, each coverage cell offers $L = 20$ channels and it is connected, by a switching subnet, to the net-sender. Border effects on mobility are neglected by ignoring mobile trajectories with paths outside the coverage set. Simulation time has been set to 3000 s for each run.

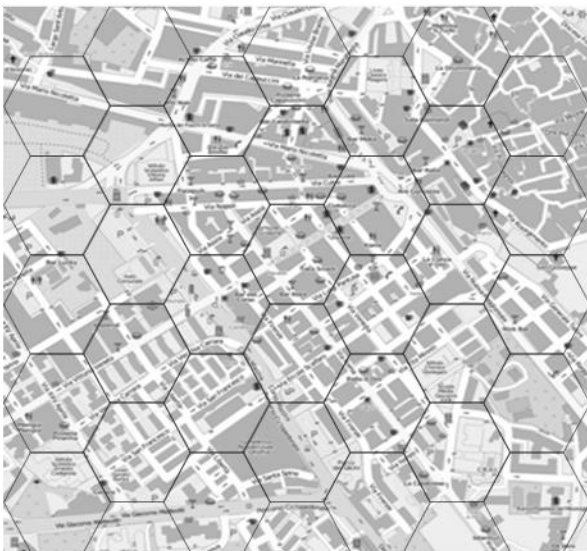


Fig. 6: Simulation map with $c = 35$, $cr_i = 160 \text{ m}$ and $L = 20$.

A first campaign of simulations has been carried out in order to obtain the appropriate training data for CHMC and DHMC models. In particular, the proper size of the training set has been investigated and Fig. 7 shows the trend of the prediction accuracy for different number of observations. Due to space limitations only the curves for $cr_i = 160 \text{ m}$ are shown; in the other cases the trend is very similar. Prediction accuracy is evaluated as the ratio

between the number of correctly predicted hand-over observations and the number of total observations: for the CHMC the correctness of prediction is evaluated on all the visited cells in the considered paths, while for the DHMC it is evaluated on all the observed hand-out directions.

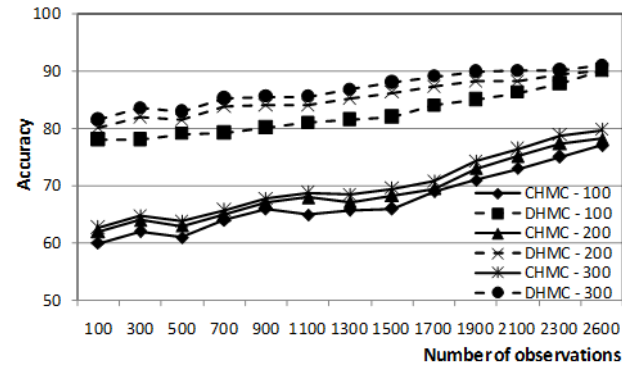


Fig. 7: Prediction accuracy for CHMC and DHMC for different training set dimensions (100, 200 and 300).

From Fig. 7 it is evident how the distributed scheme outperforms the centralized one, because each coverage cell has its own HMC and training is made only on the possible hand-out directions that belong to the specific coverage. In addition, the dimension of the training data have to be carefully chosen, in order to avoid over-fitting phenomena [9], [10]. In our case, a training set of 200 items brings the predictor to acceptable performance in terms of prediction accuracy.

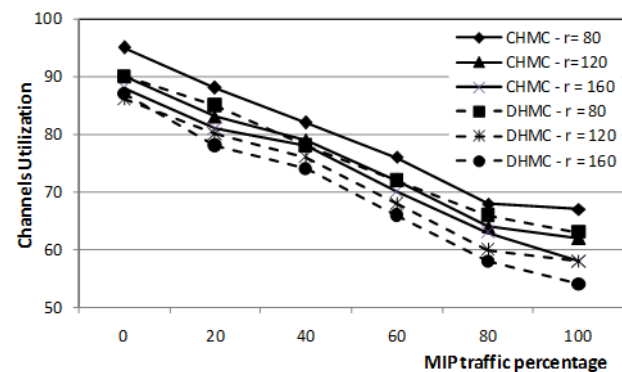


Fig. 8: Average channels utilization.

Figure 8 depicts the trend of the average channels utilization of the whole wireless system for different MIP traffic percentages: it represents the ratio between the number of channels assigned to MIP active calls and the total number of channels of the system ($cL = 35 \cdot 20 = 700$). Different percentages of MIP traffic have been considered with different values of cell radius r , with a best-effort complementary traffic (no passive reservations are made for this kind of traffic).

When MIP traffic increases, more passive reservations are made into the system, so a higher number of channels are, in-advance, reserved for the arriving mobile hosts. In this way a bandwidth wastage is introduced and channels utilization falls below 70 %. No

big differences are evident among the proposed schemes (the maximum gap is around 5 %). For larger radio coverage, channels utilization decreases due to higher quantity of mobile hosts which have to be served, with a consequent increasing of passive reservations.

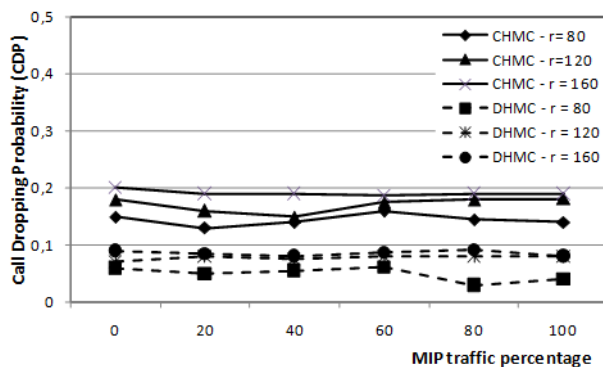


Fig. 9: Call Dropping Probability for different MIP traffic percentage and coverage radius.

The Call Dropping Probability has been depicted in Fig. 9: it does not depend on MIP traffic percentage and the distributed scheme performs better than the centralized one; for lower values of r , the DHMC makes the CDP be below 6 %. Anyway, the DHMC outperforms the CHMC scheme because the CDP is maintained below 10 %.

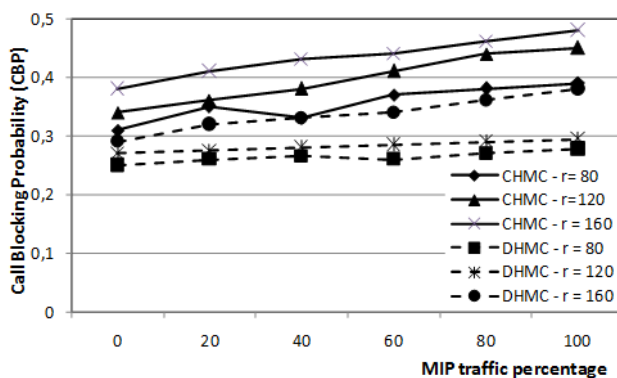


Fig. 10: Call Blocking Probability for different MIP traffic percentage and coverage radius.

Also for the CBP, the DHMC outperforms the centralized scheme as shown in Fig. 10. Higher percentages of MIP traffic lead the system to have more passive reservation requests with the same channels availability, so the call admission control denies the access more frequently; for the same reason the trend is also increasing for larger r .

5. Conclusion

In this work, a new prediction scheme is proposed for wireless cellular networks. It is based on Hidden Markov Chains (HMC) processes and aims to the guarantee of service continuity in QoS networks. Two schemes have been proposed, based on a centralized and distributed

HMC approach, in order to predict user movements among a coverage system and to make possible an adequate reservation of passive resources. The proposed idea has been validated through some deep simulation campaigns and the Distributed-HMC (DHMC) model has shown good results in terms of Prediction accuracy, CDP and CBP.

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